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A model for urban sector drivers of carbon emissions

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ABSTRACT

Urbanization as a migratory and transformative process brings changes to human activities that make a significant contribution to climate change. Carbon emissions have been steadily increasing because of rapid world population growth. This paper attempts to formulate an impact model of urbanization on carbon emissions by offering a breakdown of urban sector drivers of emissions: residential, commercial and industrial to elucidate the dynamics of variables' interaction. The model facilitates a comparative analysis of three groups of countries namely; High Income, Upper-Middle Income, and Lower-Middle Income. Key performance indicators measuring carbon emissions in each group of countries together with the EKC model were used and indicated an inverted U-shaped function between carbon emissions and GDP per capita and a linear relationship with urbanization. Further, the analysis revealed different carbon emissions and trends because of the interaction of urban sector drivers. The paper concludes with policy implications for each group of countries.

1. Introduction

Climate change is a global phenomenon that is evidenced in global warming, rising sea levels, rising average temperature, and the degradation of environmental quality. World Bank Database suggests that human activities make a huge contribution to climate change. In fact, carbon emissions have increased from 4.042 metric tons per capita in 1993 to 4.252 in 2003, and 4.972 in 2014. The Intergovernmental Panel on Climate Change (2014) report shows that carbon emissions are mainly driven by economic activity, population size, land use patterns, lifestyle, energy use, technology and climate policy.

As a migratory and transformative process, urbanization brings about changes to the socio-economic development of urban areas that require major infrastructural development, housing, transportation and industry (Martínez-Zarzoso & Maruotti, 2011). Urbanization, literally, relates to land use because all human activities require land (Long, Shao, & Chen, 2016). Residential use, together with transportation network, comprise the largest uses with an appreciable effect on the environment (Fang et al., 2018). Continued carbon emissions will lead to sustained pervasive and irreversible impacts not only on cities but also on people and ecosystems (Dodman, 2009; Kniivilä, 2004). Limiting the climate change trend would require concerted actions to reduce carbon emissions through adaptation and mitigation (Fan et al., 2006). The period between 1993 and 2011 typically exhibits a rising level of carbon emissions in the Upper-Middle Income group of countries and the Lower-Middle Income group of countries and a declining level in the High Income group of Countries. Differences in carbon emission trends arise primarily from human activities, energy consumption and economic affluence (Fig. 1). Current low carbon metrics confirm the above trends at global and local scales.

Further, high carbon emission has been a global issue that requires international cooperation to mitigate its impacts. This paper attempts to specify the primary contributors of carbon emissions that operate at a local scale but have a country, regional or global impact.

The authors built a model that dissects urbanization into sectors: residential, commercial and industrial and then examined their impact in three groups of countries: High Income (HIC), Upper-Middle Income (UMC), and Lower-Middle Income (LMC). Although there are many studies on stochastic impacts by regression on population, affluence and technology at local and national scales such as Franco, Mandla, and Ram Mohan Rao, (2017); Roy, Basu, and Pal, (2017) and Yang et al. (2017), this study affords a global perspective by offering a breakdown on the various urban sector drivers of emissions in High Income, Upper-Middle Income, and Lower-Middle countries. The urban sector is often considered a single sector in most impact and emissions studies at the national and even global scale, a sector that has been dissected in the proposed model to elucidate the dynamics of variables' interaction. To emphasize the importance of urban sector drivers, the authors have named the model the Urban Sector Drivers of Carbon Emissions Model (USDM). The authors hope that the proposed model will contribute to the wider body of research on sustainable cities and communities. The model can be deployed to test local, country or global datasets and

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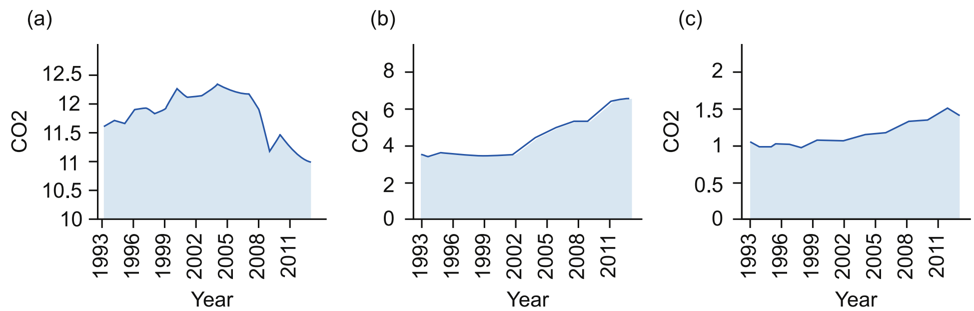

Fig. 1. Carbon emissions *(in billion metric tons)*; (a) High Income group of Countries; (b) Upper-Middle Income group of countries; (c) Lower-Middle Income group of countries.

draw comparisons and thereby inform future research. It is an endeavour to support sustainable development goals and the agenda of both the United Nations and World Bank.

2. Literature review

Research studies seeking to measure the impact of urbanization on carbon emissions are extensive and persuasive. Differences in models, scopes and results arise primarily from the variables used. Most models tend to deal with cities and individual countries. Early studies that attempted to examine the relationship between human activities and carbon emissions were conducted by, amongst others, Ehrlich et al. (1971) who put forth a model known as (IPAT), which examines the key drivers of anthropogenic environmental consequences. This model was built based on three basic factors: population (P), affluence (A) and technology (T). There is a strong interconnection between these factors. If a study reveals that affluence and technology are constant, while population is increasing, it could not conclude that population is the sole cause of impact because the other two variables influence change at a certain level (York, Rosa, & Dietz, 2003).

Dietz and Rosa (1997) improved analytical methods by adding the influence of technology on carbon emissions. Likewise, Zhu and Peng (2012) explained the effects of population growth on carbon emissions using quantitative evaluation. IPAT model was advanced by adding the principle of stochastic form by multiple regression of population, affluence and technology and became the STIRPAT model (Dietz & Rosa, 1997).

Further research has investigated the role of energy consumption and population structure on carbon emission (Wu et al., 2016). Additional methods have been added to increase accuracy of the results such as Kaya, U-Kaya, and Kuznet Curve which is abbreviated as EKC model (Martínez-Zarzoso & Maruotti, 2011). By referring to the EKC concept, carbon emissions are expected to maintain a positive relationship with the GDP per capita and trade openness until a threshold is reached. Thereafter, a negative relationship begins appearing. Zhang and Tan (2016) found a positive correlation between population and carbon emissions. Moreover, Martínez-Zarzoso and Maruotti (2011) noted there is an inverted U-shaped function, where urbanization was initially reduced by carbon emissions, but after reaching a threshold, it begins increasing with affluence. A large gap between urban and rural GDP per capita eventually leads to a significant increase of carbon emissions (Wu et al., 2016). If appropriate land control measures are in place, a positive correlation of carbon emission with residential and transportation uses is expected (Wang & Zhao, 2017). Green technology adoption positively influences carbon emission which is indicated by an inverted U-shaped function in EKC models (Yang et al., 2015).

Moreover, the causal relationships between environmental pollution, trade openness and economic growth have instigated studies of on the impact of carbon emissions on global energy system and pattern. Again, EKC models have provided better understanding of environmental consequences arising from international trade and economic growth. Unfortunately, differences in income levels across countries have received scant attention in previous research. This study attempts to bridge this gap by examining the relationships between carbon emission, trade liberalization and economic growth in different groups of countries.

Carbon emissions from fuel combustions rose and dominated global trends overcoming electricity and heat production, the major sources of carbon emissions between 1990 and 2010 (Bakirtas & Akpolat, 2018). Most research studies have concluded that urbanization has a strong relationship with transportation demand which involves firm agglomeration and urban densification to encourage green public transportation development (UN-Habitat, 2016; Zhou et al., 2015).

Using World Bank classification (World Bank, 2015), data of High Income, Upper-Middle Income, and Lower-Middle-Income groups of countries were sampled and analysed. Low Income group of countries were excluded from this investigation because their impact on carbon emissions is nearly negligible. The list of countries in each group can be seen in the Appendix A, Table A1.

Carbon emissions originate from three sources: (1) CO_2 from all sectors, (2) CO_2 from residential and commercial sectors, and (3) CO_2 from industrial and other sectors. This classification schema is necessary to clarify urban sector contributors that have considerable interactions in the modelling process.

3. Methods

The research methodology is constructed on three interrelated components: (1) theoretical and methodological framework, (2) statistical analyses and (3) model testing and comparison (Fig. 2). The formulation process of the proposed USDM model can be shown as follows:

First, STIRPAT which has been widely used to measure the impact of human activities on the environment is used. The initial STIRPAT model has been defined by (Eq. (1)):

$$I_i = \alpha P_i^{\beta 0} A_t^{\beta 1} T_i^{\beta 2} \varepsilon_i \quad (1)$$

where I_i, P_i, A_t, and I_t are referred to as environmental impact, population, affluence, and technology in country *I*. Parameters α and β are estimated, and i_t is the random error. Affluence *A* is measured by the GDP per capita, and *T* which is denoted as technology relates to the percentage of industrial activity regarding total production.

Second, the authors employed a standard EKC regression model after reviewing the studies of Martínez-Zarzoso and Maruotti (2011); Zhang, Yi, and Li, (2015); Shahbaz et al. (2016) who integrated STIRPAT and EKC models to measure the long-term impact of economic factors on the environment (Eq. (2)):

$$\ln(E/P)_{it} = \alpha I + \gamma t + \beta_y \ln Yi_t + \beta_Y{}^2 \ln Y_t^2 + \varepsilon_t \quad (2)$$

Where *E* is emissions, *P* is population, *Y* is GDP per capita, *ε* is random error, and *ln* is natural logarithm. The first two terms on the model are intercept parameters that vary across countries or regions *i*

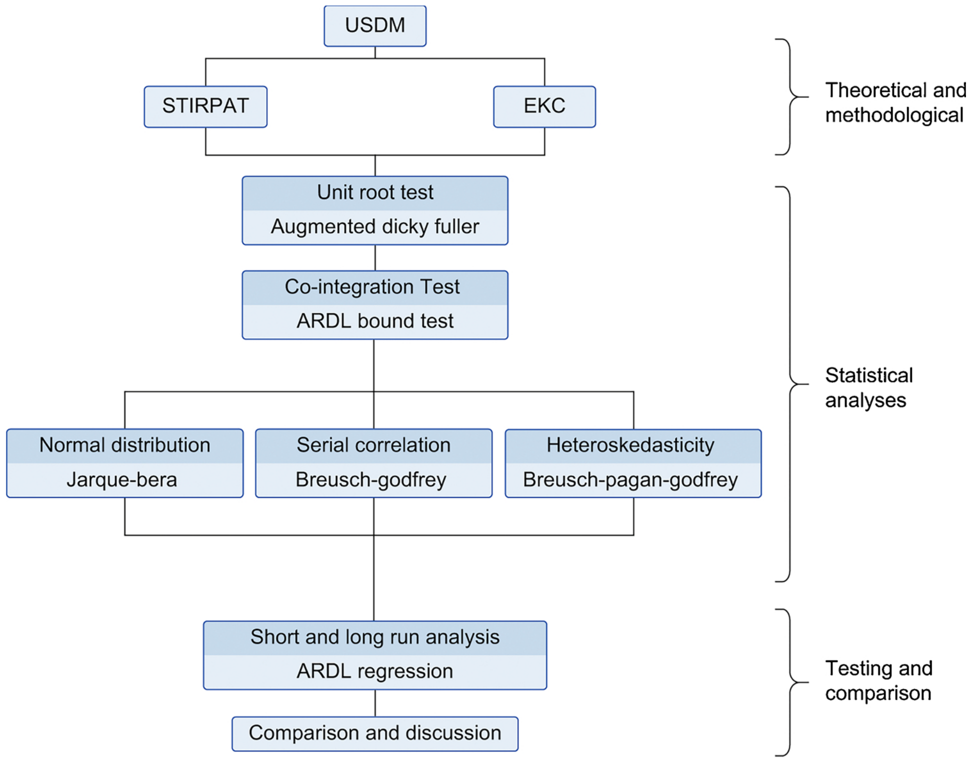

Fig. 2. Research Methodology.

and years *t*. According to Zhu et al. (2016) we can assume that the variable *ln(E/P)* is the impact (*I*) on the environment An inverted U-shaped function is assumed which according to Pacheco-borja (2016) can be accommodated by the EKC model to indicate a nonlinear relationship between two variables.

Building on the framework of Choi, Heshmati, and Cho, (2010), the authors added environmental degradation and GDP per capita variables to the proposed model to determine the influence of land use on CO_2 emissions. Where lnC_t represents carbon emissions in *t* year, the model can be expressed in Equation (3).

$$\ln C_t = \beta_1 + \beta_{UP} \ln UP_t + \beta_y \ln Y_t + \beta_Y{}^2 \ln Y_t^2 + \beta_{EC} \ln EC_t + \beta_I \ln T_t + \mu_t \quad (3)$$

where lnC_t represents carbon emissions in *t* year. The variables that have been selected are frequently used in global policies, namely; urban population (percentage of people live in urban area), affluence (GDP per capita), energy consumption (kg oil equivalent per capita) and trade openness measured by added value of industry in US$ dollars. Further, using the proposed USDM model for comparative analysis, carbon emissions were divided into two categories: (1) $lnCR_t$ which represents CO_2 emissions from residential, commercial and public service sectors; (2) $lnCOT_t$ which represents CO_2 emissions from industrial and other sectors.

Third, the proposed USDM model has been used to conduct long-run analysis using the "Autoregressive-Distributed Lag" ARDL regression which would facilitate testing co-integration among the variables in timeline data. Examining the long-run relationships, because of equilibrium forces, means that time series are bound together. The ARDL test is employed to draw conclusive inference without knowing whether the variables are stationery at level *I(0)* or first level *I(1)((Eq.4))*.

$$\Delta\ln C_t = \beta_0 + \Sigma\beta_i\, \Delta C_{t\text{-}i} + \Sigma\gamma_j \Delta\ln UP_{1t\text{-}j} + \Sigma\gamma_j\, \Delta\ln Y_{t\text{-}j} + \Sigma\gamma_j\, \Delta\ln Y^2{}_{t\text{-}j} + \Sigma\gamma_j\, \Delta\ln EC_{t\text{-}j} + \Sigma\gamma_j\, \Delta\ln T_{t\text{-}j} + \theta_0 \ln C_{t\text{-}1} + \theta_1 \ln UP_{t\text{-}1} + \theta_2 \ln Y_{t\text{-}1} + \theta_3 \ln Y^2{}_{t\text{-}1} + \theta_4 \ln EC_{t\text{-}1} + \theta_5 \ln T_{t\text{-}1} + e_t \quad (4)$$

Fourth, unit root test was used to examine whether the data are stationery at level *I(0)* or at the first difference level *I(1)*. Co-integration test is intended to ensure that the variables have long-term relationships. Normal distribution, serial correlation and heteroscedasticity distribution tests were necessary for ARDL regression to simulate short and long-run analysis. Data between 1973 and 2013 were extracted from the World Bank (2015) and then tabulated for analysis. This test is supported Zhang et al. (2015) and Shahbaz et al. (2016) who measured the impact of urbanization using an ARDL model in China and Malaysia respectively. While their models are country specific, the proposed model (USDM) affords a global perspective for different income groups of countries: High Income, Upper-Middle Income, and Lower-Middle Income. USDM's limitations arise from the utilization of inherent variables in the EKC and STIRPAT models. Transport and technology have not been accommodated in the USDM model. Thus, they fall beyond the scope of this investigation. The studies of Lehmann (2012); Chunark et al. (2015) and Liu and Wang (2017) could be consulted for further research on transport and technology impacts.

4. Results

Five statistical analyses were made before ARDL regression, namely; unit root, co-integration, normal distribution, serial correlation and heteroscedasticity tests. Monitoring of small shifts in the process mean was charted using a cumulative sum test (CUSUM).

4.1. Unit root test

The authors have initiated the analysis with unit root test for High Income, Upper-Middle Income, and Lower-Middle Income groups of countries at level *I(0)* and the first level *I(1)*. Dicky-Fuller method was employed, the result of which is shown in Table 1.

In all groups of countries, some variables are stationery at level *I(0)* and others are stationery at the 1st difference level *I(1)*. While the ln*UP* variable is stationery at level *I(0)*, ln*COT* and ln*EC* are stationery at the first level *I(1)*. No variable is stationery at 2nd difference level *I(2)*.

Table 1
Unit root test of High Income, Upper Middle Income, and Lower Middle Income groups of countries.

Variables	At level		At 1 st difference	
	T-statistic	*Time break*	*T-statistic*	*Time break*
1. High income group of countries				
ln Ct	−2.1452	2008	−5.7643*	2009
ln CRt	−2.2404	1987	−6.3975*	1998
ln COTt	−2.8906	1989	−8.6337*	2012
ln UPt	−2.9771	2000	−5.0432*	2000
ln Yt	−4.3434	1985	−5.2730*	1995
ln Y2 t	−3.9207	1985	−5.1690*	1995
ln ECt	−2.7233	1986	−5.8140*	2009
ln Tt	−2.8137	2003	−6.8978*	2009
2. Upper middle income group of countries				
ln Ct	−4.3464	2002	−5.7872*	2002
ln CRt	−2.1178	1989	−11.384*	1990
ln COTt	−2.6756	1994	−9.5451*	2000
ln UPt	−7.0512*	2000	–	–
ln Yt	−3.3738	2003	−6.0541*	2002
ln Y2 t	−2.9112	2003	−6.2310*	2002
ln ECt	−2.0300	1989	−15.637*	1990
ln Tt	−2.2868	2002	−7.2987*	2009
3. Lower middle income group of countries				
ln Ct	−2.7128	2003	−6.0624*	1992
ln CRt	−1.7466	2004	−5.9742*	1990
ln COTt	−4.5155*	1994	–	–
ln UPt	−3.5754	2002	−7.6457*	1990
ln Yt	−4.1275	2003	−5.6964*	1998
ln Y2 t	−3.5197	2003	−5.5922*	1998
ln ECt	−4.6085*	1989	–	–
ln Tt	−2.9228	2003	−6.0908*	2002

*Note: *, **, and *** represent significance at 1%, 5%, and 10% levels respectively.* ***UP** : Urban Population; **Y** : GDP per Capita; **EC** : Energy Consumption; **T** : Trade Openness.*

4.2. Co-integration test

To ensure the population from which data were sampled are in the best fit model, bounds test was conducted to examine the co-integration between variables. An F-test with lower and upper bounds' critical values was also made (Table 2).

F-statistics in all models exceed upper bounds *I(1)* at 1% significance level except lnC_t in High Income groups where the F-statistic value lies between *I(0)* and *I(1)* at 10% significance level. Part of the requirements that have been fulfilled before conducting ARDL was to ensure that the proposed regression model, USDM, follows normal distribution, and is free from serial correlation and heteroscedasticity.

4.3. Normal distribution test

A normality test of the dataset was carried out using Jarque-Bera, the result of which shows that generally datasets of all groups of countries are normally distributed (Table 3).

Table 2
ARDL Bounds Test.

Income groups	**F-statistics**		
	ln Ct	**ln CRt**	**ln COTt**
HIC	2.5616***	5.2715*	5.6053*
UMC	6.9692*	3.6286*	8.9574*
LMC	11.2966*	7.2121*	8.8584*
Critical values	**Lower bounds *I(0)***	**Upper bounds *I(1)***	
10%	2.08	3	
5%	2.39	3.38	
1%	3.06	4.15	

*Note: *, **, and *** represent significance at 1%, 5%, and 10% levels respectively.*

Table 3
Jarque-Bera Normal Distribution Test.

Income Group	ln Ct		ln Crt		ln COTt	
	JB-Value	*Probability*	*JB-Value*	*Probability*	*JB-Value*	*Probability*
HIC	2.9963	0.2235	1.0144	0.6022	6.2719	0.0435
UMC	1.1434	0.5646	0.0557	0.9726	0.6142	0.7356
LMC	0.1233	0.9402	2.2429	0.3258	0.3663	0.8326

Table 4
Breusch-Godfrey Serial Correlation LM Test.

Income Group	ln Ct		ln CRt		ln COTt	
	F-Statistic	*DB*	*F-Statistic*	*DB*	*F-Statistic*	*DB*
HIC	8.1925	2.9350	4.5536	2.2179	1.9597	2.1467
UMC	3.5201	2.2613	6.8856	2.2737	6.5147	2.2518
LMC	0.9647	2.0872	2.4949	2.2999	0.8094	2.2757

4.4. Serial correlation test

The Breusch-Godfrey serial correlation test was employed in the proposed modelling process showed by Durbin-Watson (DB) value in Table 4. To ascertain the above result, the authors used an auto correlation test which showed that all datasets are without serial correlation (Appendix A, Table A2).

4.5. Heteroscedasticity tests

Using the Breusch-Pagan-Godfrey test, the variance of errors from a regression was made. Table 5 shows that datasets of all groups of countries are free from heteroscedasticity.

The above five tests were followed by a CUSUM test to monitor shifts in the process mean for High Income, Upper-Middle Income, and Lower-Middle Income groups of countries. Fig. 3 shows that the proposed USDM model is quite stable for long-term analysis.

4.6. Long-run analysis

Using E-views, USDM model formulations have been tested for High

Table 5
Heteroscedasticity Test: Breusch-Pagan-Godfrey.

Income Group	ln Ct		ln CRt		ln COTt	
	F-Statistic	*Probability*	*F-Statistic*	*Probability*	*F-Statistic*	*Probability*
HIC	0.5152	1.0000	0.5971	1.0000	0.4679	1.0000
UMC	0.3738	1.0000	0.8615	1.0000	0.8044	1.0000
LMC	1.3347	1.0000	0.6364	1.0000	1.0726	1.0000

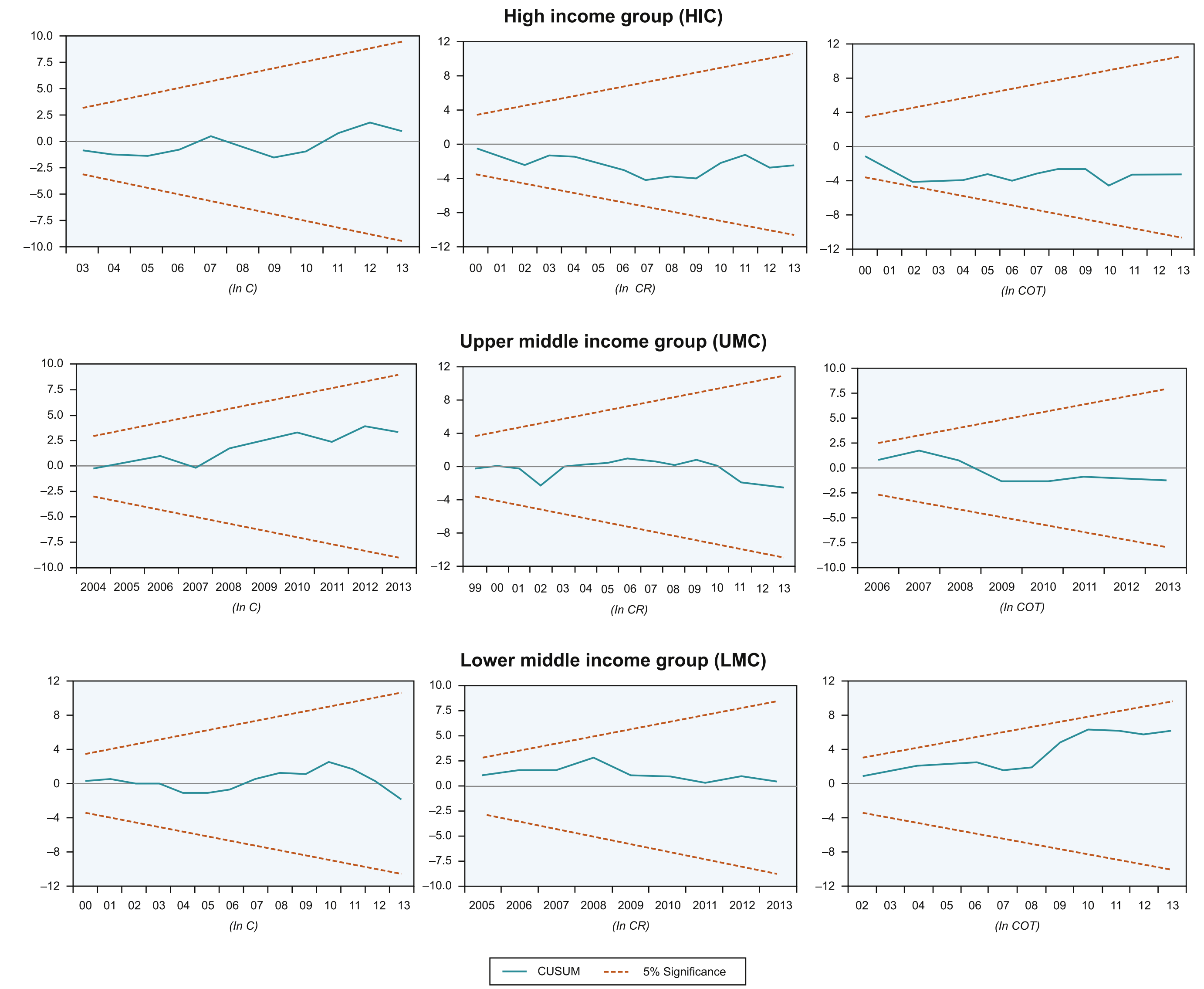

Fig. 3. Cumulative Sum (CUSUM) chart of recursive residuals for High Income, Upper-Middle Income and Lower-Middle Income groups of countries.

Table 6
Long-run analysis of High Income, Upper Middle Income, and Lower Middle Income groups of countries.

Variables	HIC			UMC			LMC		
	ln Ct	ln CRt	ln COTt	ln Ct	ln CRt	ln COTt	ln Ct	ln CRt	ln COTt
Constant	−22.880	18.707*	46.540*	−15.787*	−1.935	−9.039*	−2.045**	−0.074	6.584
ln UPt	4.543	−2.473*	−15.825*	−1.388	0.660	0.202	1.572*	−0.433	−3.732*
ln Yt	0.621	−0.225	1.395	7.350**	3.611*	4.865*	0.272	−1.745	−0.324
ln Y2 t	−0.032	0.012	−0.106	−0.362**	−0.182*	−0.216*	0.003	0.068	−0.007
ln ECt	1.251*	−0.474*	−1.680*	−0.363	−0.527	1.016*	0.403*	−1.17*	3.816*
ln Tt	−0.263	−0.015	1.111*	−0.787**	−1.003*	−1.949*	−0.248*	0.626*	−0.476**
R2	0.996	0.993	0.993	0.999	0.997	0.997	0.998	0.996	0.971
F-statistic	129.134	99.283	92.110	466.714	238.934	109.563	339.974	89.900	17.254

*Note: *, **, and *** represent significance at 1%, 5%, and 10% levels respectively.*
***UP**: Urban Population; **Y** : GDP per Capita; **EC** : Energy Consumption; **T** : Trade Openness.*

Income, Upper-Middle Income, and Lower Middle Income groups of countries (Table 6).

The High Income group of countries (HIC) shows that energy consumption (EC) has a significant contribution to carbon emissions. If energy consumption (EC) increases by 1%, the total carbon emissions (C) increases by 1.25%. Urbanization has a pronounced impact on carbon emissions from residential and commercial uses (CR) and industrial uses (COT). Put simply, every 1% increase in urbanization would lead to a 2.47% decrease in carbon emissions from residential and commercial uses and 15.83% from industrial uses respectively.

Table 7
Short-run analysis of High Income, Upper-Middle Income, and Lower-Middle Income groups of countries.

Variables	HIC			UMC			LMC		
	ln Ct	ln CRt	ln COTt	ln Ct	ln CRt	ln COTt	ln Ct	ln CRt	ln COTt
Constant	0.783*	1.347*	–0.102	–0.827*	–0.803*	0.827*	0.443*	0.280**	0.599*
ln UPt	–3.500*	21.041**	45.367*	4.041	0.231	–0.864	4.347	18.469***	23.463
ln Yt	–1.814*	–3.132	2.297	3.225*	–3.575*	–11.23*	–1.221*	2.406*	–12.687*
ln Y2 t	0.095**	0.165***	–0.124	–0.178*	0.222*	0.649*	0.080**	–0.167*	1.061*
ln ECt	–0.916*	0.667*	1.310**	–0.147*	–	–1.719*	–0.325*	–0.081	–3.629*
ln Tt	0.013	0.001	0.578*	–0.537*	0.159**	2.441*	0.185*	–0.425	–1.239*
R2	–0.343*	–2.759*	–1.396*	0.546*	–0.360*	–2.176*	–1.539*	–0.926*	–1.642*
F-statistic	0.783*	1.347*	–0.102	–0.827*	–0.803*	0.827*	0.443*	0.280**	0.599*

*Note: *, **, and *** represent significance at 1%, 5%, and 10% levels respectively.*
***UP**: Urban Population; **Y** : GDP per Capita; **EC** : Energy Consumption; **T** : Trade Openness.*

Conversely, trade openness (T) has a positive impact on industry (COT), where every 1% increase of trade openness leads to a 1.11% increase in carbon emissions. GDP and carbon emission function are U-shaped and statistically significant as indicated by positive $(Y)_t$ and negative $(Y_t^2.)$ coefficients.

The Upper-Middle Income group of countries (UMC) manifests a pronounced effect of GDP on carbon emissions (Y_t, Y_t^2 and T_t). The opposite holds good for trade openness (T) which has a negative impact. An increase of trade openness by 1% would decrease energy consumption from residential and industrial uses (C) by 0.7%, 1%, and 1.94% respectively.

The Lower-Middle Income group of countries (LMC) displays a significant impact on energy consumption (EC) and trade openness (T) on all carbon emission sources. Likewise, trade openness has a prominent positive correlation with industry (0.62%).

4.7. Short-run analysis

Again E-views was used to test the proposed USDM model formulations in the short run for High Income, Upper-Middle Income, and Lower-Middle Income groups of countries (Table 7).

The High Income group of countries shows a significant impact of GDP on carbon emissions. The biggest effect comes from industry (COT), where a 1% of GDP increase will potentially raise carbon emissions by 1.38%. Urbanization, on the other hand, exhibits a negative effect on carbon emissions across the board.

The Upper-Middle Income group of countries exhibits a negative correlation of GDP with industry (COT), where an increase of 1% in the former leads to an 11.23% rise in the latter. Surprisingly, the urban population does not have a prominent impact on the level of carbon emissions. In fact, *ln* C_{t-1} indicates that a mere increase of 1% in carbon emissions would result in 0.8% reduction by reason of commercial uses.

The Lower-Middle Income group of countries features a significant correlation of GDP with carbon emissions from *C* (-1.22%), *CR* (2.7%) and *COT* (-12.6%). When GDP is high, carbon emission from all sources will be low. Carbon emissions *(C)* from industry *(COT)* is appreciably influenced by all variables, especially urban population, whereby an increase of 1% in urban population would lower carbon emissions by 18.5%.

Generally speaking, GDP *(Y)* in the above three groups of countries indicates elasticity that can be noted from the positive-negative coefficients between Y and Y^2. The coefficient of CointEq_{t-1} shows a positive co-integration of carbon emission sources.

To examine the relationship between CO_2 and GDP per capita, the authors have employed the EKC model, the result of which can be seen in Fig. 4.

Carbon emissions show nonlinear growth. The High Income group of countries has a U-shaped function for residential and commercial uses (CR) and an inverted U-shaped function for industrial activities (COT). In Upper-Middle Income group of countries, all sectors maintained inverted U-shaped curves, which implies that at a certain point, GDP per capita growth will reach a turning-point beyond which carbon emissions start dwindling. The Lower-Middle Income group of countries features a nonlinear relationship of carbon emissions with industry (COT) and a linear relationship with GDP. This was further explored by Choi et al. (2010), who tried to achieve targets of the economy whilst keeping a low pollution through a "tunnel effect" strategy.

5. Discussion

In examining the impact of urbanization on carbon emissions, the general approach was: "*global to local and general to specific*". Detecting anomalies in time series data was fraught with difficulties but has been solved by data normalization technique and a series of statistical tests. The dynamics of variable's interaction in the proposed USDM have shown an inverted U-shaped function between carbon emissions and GDP per capita and a linear relationship with urbanization. The ARDL regression result in Table 6 shows that urban population and energy consumption have a significantly positive correlation with carbon emissions in High Income, Upper-Middle Income, and Lower-Middle Income. Increased urban population appears to encourage energy demand inside urban areas and, subsequently, increase carbon emissions, especially in High Income and Lower-Middle Income countries. This result reinforces Wu et al. (2016) findings that high urbanization rate and energy consumption lead to increased carbon emissions.

In the Upper-Middle Income group of countries, GDP per capita is the most significant carbon emissions driver. This is similar to the finding of Shahbaz et al. (2016) who examined urbanization in Malaysia and concluded that economic growth is the major contributor to carbon emissions. The same holds good for Russia, the economy of which is predominantly driven by mining and petroleum (Pao, Yu, & Yang, 2011). In general, the Upper-Middle Income group of countries is dominated by countries that are largely dependent on tourism. In this sector, carbon emissions come from transportation and the need for higher mobility.

5.1. CO_2 from residential and commercial sectors

There is a paucity of research on the primary source of carbon emission sources at a local scale that can be projected to a global scale. By, contrast, this paper has examined the principal drivers of carbon emissions under two sectors: (1) residential and commercial uses and (2) industrial activities in countries of different income groups, CO_2. The result shows that carbon emissions from the residential and commercial sector tend to decrease in all groups of countries in the long run. This finding gains support from Ahlering, Fargione, and Parton, (2016) study, in which they concluded that 93% of the residential sector's direct emissions come from fuel combustion, primarily for heating and cooking.

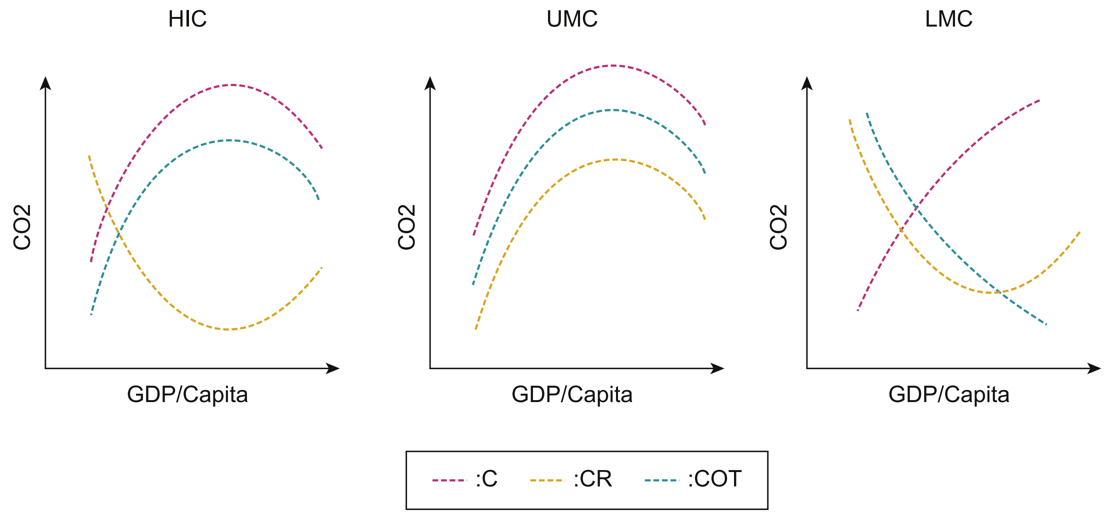

Fig. 4. Visualisation of EKC model in High Income, Upper-Middle Income, and Lower-Middle Income groups of countries.

They go on to say that the commercial sector contributes 60% of direct emissions originating from on-site fossil fuel combustion.

Urban areas in developed countries use less energy per capita than rural areas. District heating in high density areas together with inefficient transportation seem to be the underlying reason (Kronenberg, 2009). However, this result contradicts Lin et al. (2017) findings that population and GDP per-capita lead to carbon mission increase. In developing countries, the lack of efficient public transportation and greater accessibility of residents to energy appear to mark a pronounced effect on the country's energy footprint. Continuous economic growth is likely to lead to increased global demand for energy and higher carbon emissions if energy-efficient products and practices are not in place. By considering the reduction of energy demand and emissions, there are some efforts that should be considered, such as renewable energy usage, smart grid system and power plant decentralisation.

5.2. Carbon emissions from industrial and other sectors

The long run analysis result shows that industrial activities in High Income group of countries appears to decrease carbon emissions by reason of economic development, a finding that has been reported by Yang et al. (2015). On the contrary, carbon emissions in the Upper-Middle Income and Lower-Middle Income group of countries seem to increase owing to higher industrial activities, a finding that is similar to the conclusions of Wu et al. (2016). The industrial sector appears to raise energy consumption which encompasses wide-ranging activities such as manufacturing, mining, and construction. Carbon emissions are produced by diverse processes such as combustion of fossil fuel for heating and cooking and other industrial activities (Sadorsky, 2014).

Urban population and energy consumption have a negative correlation with carbon emissions from the industrial sector. In High Income group of countries, trade openness causes carbon emissions to increase (Fig. 5). The findings of this research is similar to the conclusions of Zhao, Burnett, and Fletcher, (2014), who examined the impact of industrial activities on carbon emissions in China, the largest carbon emitter in the world.

By contrast, the United States reduced carbon emissions from industrial processes by 23% between 1990 and 2012, despite an increase in industrial output by 55% by reason of improved carbon-intensive technology, increased efficiency, and changes of the US economy from manufacturing to services (Olivier, Muntean, & Peters, 2015).

Again, the findings of this research suggest that the Lower-Middle Income group of countries should improve technologies of industrial development to reduce intensive energy usage. Bakirtas and Akpolat (2018) and Lin et al. (2017) are of the opinion that technology must be supported by additional investment or cross-subsidy from the High Income and Upper-Middle Income groups. Electricity consumption for industrial purposes uses coal as its principal source of fuel; attempts are

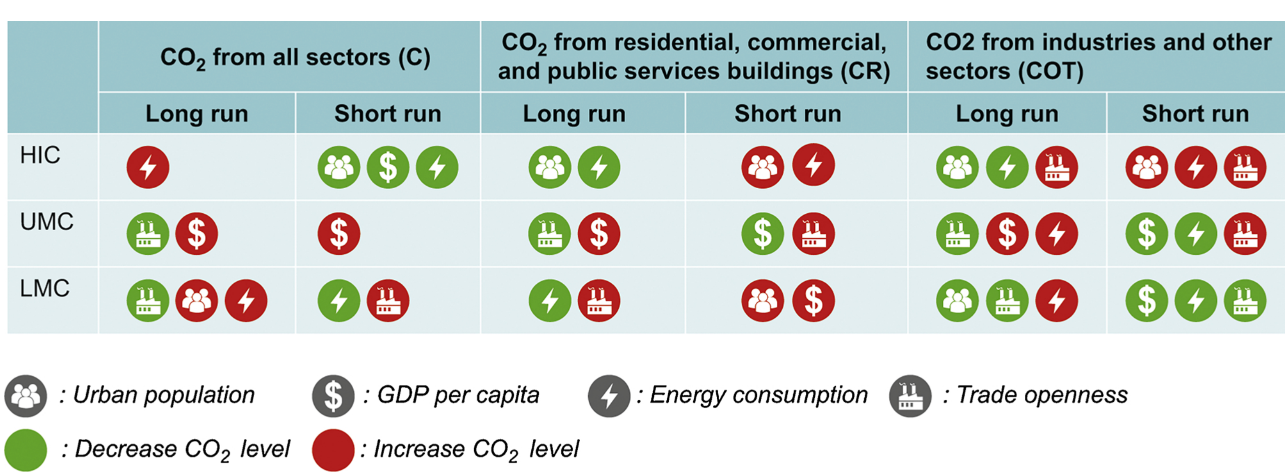

Fig. 5. Significant variables' effect on each group of countries based on the long and short run analysis.

being made to use natural gas, wind and solar energy to decrease carbon emissions. Wu et al. (2016) recommend that Lower-Middle Income should focus on operations, environmental sustainability, recycling and reuse at the enterprise level. Likewise, the adoption of eco-infrastructure will help communities to pursue the target of economic development, minimize environmental degradation, and encourage investors to move towards green industry.

6. Conclusions

This study has investigated the impact of urbanization on carbon emissions focusing on residential, commercial and industrial sectors with a comparative analysis on High Income, Upper-Middle Income and Lower-Middle Income groups of countries together with the drivers of emissions in these countries. An impact model of urban sector drivers on carbon emissions (USDM) has been formulated to afford a new perspective on the relationship between urbanization, economic factors and carbon emissions for the above three groups of countries. The proposed model is not an isolated piece of research, but an exposition of urban dynamics of variables' interaction that have not been investigated in similar impact studies. By measuring the impact of urban sector drivers locally and globally, the model expands our understanding of local sustainability. Time series data are not only normalized and rigorously tested for anomalies, but also dissected into urban sectors, a technique that led to more specificity in pinpointing the primary sources of carbon emissions.

Further, an ARDL test was conducted that has clearly shown that in High Income countries, urban population and energy consumption have a positive correlation with carbon emissions, whereas GDP per capita has a negative association. On the contrary, GDP and urban population in the Upper-Middle Income and Lower-Middle Income groups of countries have a positive interdependence. Most carbon emissions originating from the residential, commercial and public sectors are strongly influenced by energy consumption and trade openness. Urbanization displays an inverse function with energy consumption and trade openness in High Income and Lower-Middle Income groups of countries, but positive correlation in the Upper Middle-Income group of countries. This might be attributed to the propensity of firms to locate industrial activities in those countries. Moreover, carbon emissions have been elastic in all groups of countries. The implication being that Lower-Middle Income group of countries should entertain environment-friendly industrial policies to attract business from High Income and Upper-Middle-Income firms.

The authors hope that the proposed USDM model could inform future sustainability and urban planning policies. It could easily predict the real contributors of carbon emissions in any geographical unit: city, country or globe. Moreover, the model could measure effect of future development. Additional variables, such as transportation could be added to the USDM to build more comprehensive models without much adaptation. By integrating the proposed model with land use pattern or typical urban structure the low carbon city plan could be pursued and development policies reviewed.

Appendix A

Table A1
List of groups of countries by income.
Source: World Bank, 2013

1. High income group of countries			
• Andorra	• Estonia	• Liechtenstein	• Singapore
• Antigua and Barbuda	• Faroe Islands	• Lithuania	• Saint Maarten
• Aruba	• Finland	• Luxembourg	• Slovak Republic
• Australia	• France	• Macao SAR, China	• Slovenia
• Austria	• French Polynesia	• Malta	• Spain
• Bahamas, The	• Germany	• Monaco	• St. Kitts and Nevis
• Bahrain	• Gibraltar	• Nauru	• St. Martin
• Barbados	• Greece	• Netherlands	• Sweden
• Belgium	• Guam	• New Caledonia	• Switzerland
• Bermuda	• Hong Kong	• New Zealand	• Taiwan
• British Virgin Islands	• Hungary	• Northern Mariana Islands	• Trinidad and Tobago
• Brunei Darussalam	• Iceland	• Norway	• Turks and Caicos Island
• Canada	• Ireland	• Oman	• United Arab Emirates
• Cayman Islands	• Isle of Man	• Poland	• United Kingdom
• Chile	• Israel	• Portugal	• United States
• Croatia	• Italy	• Puerto Rico	• Uruguay
• Curacao	• Japan	• Qatar	• Virgin Islands
2. Upper middle income group of countries			
• Albania	• Costa Rica	• Jordan	• Paraguay
• Algeria	• Cuba	• Kazakhstan	• Peru
• American Samoa	• Dominica	• Lebanon	• Romania
• Angola	• Dominican Republic	• Libya	• Russian, Fed
• Argentina	• Equatorial Guinea	• Macedonia, FYR	• Serbia
• Azerbaijan	• Ecuador	• Malaysia	• South Africa
• Belarus	• Fiji	• Maldives	• St. Lucia
• Belize	• Gabon	• Marshall Islands	• Suriname
• Bosnia and Herzegovina	• Georgia	• Mauritius	• St. Vincent and the Grenadines
• Botswana	• Grenada	• Mexico	• Thailand
• Brazil	• Guyana	• Montenegro	• Turkey
• Bulgaria	• Iran, Islamic Rep.	• Namibia	• Turkmenistan
• China	• Iraq	• Palau	• Tuvalu
• Colombia	• Jamaica	• Panama	• Venezuela, RB

(*continued on next page*)

Table A1 (*continued*)

3. Lower middle income group of countries

- Armenia
- Bangladesh
- Bhutan
- Bolivia
- Cabo Verde
- Cambodia
- Cameroon
- Congo, Rep.
- Cote d'lvore
- Djibouti
- Egypt, Arab Rep
- El Salvador
- Ghana
- Guatemala
- Honduras
- India
- Indonesia
- Kenya
- Kiribati
- Kosovo
- Kyrgyz Republic
- Lao PDR
- Lesotho
- Mauritania
- Micronesia, Fed. Sts.
- Moldova
- Mongolia
- Morocco
- Myanmar
- Nicaragua
- Nigeria
- Pakistan
- Papua New Guinea
- Philippines
- Samoa
- Sao Tome and Principe
- Solomon Island
- Sri Lanka
- Sudan
- Swaziland
- Syrian, Arab Rep
- Tajikistan
- Timor Leste
- Tonga
- Tunisia
- Ukraine
- Uzbekistan
- Vanuatu
- Vietnam
- West Bank and Gaza
- Yemen, Rep
- Zambia

Table A2

Auto-Correlation Test Results.

High income group (HIC)

Date: 03/29/17 Time: 23:03
Sample: 1973 2013
Included observations: 37
Q-statistic probabilities adjusted for 4 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	−0.509	−0.509	10.402	0.001
2	0.140	−0.162	11.208	0.004
3	−0.219	−0.303	13.247	0.004
4	0.168	−0.122	14.475	0.006
5	0.008	0.045	14.478	0.013
6	−0.191	−0.261	16.173	0.013
7	0.225	0.040	18.612	0.009
8	−0.292	−0.266	22.861	0.004
9	0.249	−0.141	26.058	0.002
10	−0.216	−0.195	28.558	0.001
11	0.367	0.170	36.026	0.000
12	−0.324	−0.089	42.092	0.000
13	0.003	−0.270	42.092	0.000
14	0.141	−0.011	43.343	0.000
15	0.014	0.064	43.356	0.000
16	−0.138	−0.353	44.665	0.000

*Probabilities may not be valid for this equation specification.

(lnC)

Date: 03/29/17 Time: 23:00
Sample: 1973 2013
Included observations: 37
Q-statistic probabilities adjusted for 4 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	−0.405	−0.405	6.5733	0.010
2	−0.041	−0.245	6.6411	0.036
3	−0.242	−0.460	9.1264	0.028
4	0.125	−0.371	9.8071	0.044
5	0.126	−0.210	10.522	0.062
6	0.036	−0.121	10.583	0.102
7	−0.174	−0.264	12.039	0.099
8	0.003	−0.275	12.039	0.149
9	0.132	−0.086	12.933	0.166
10	−0.004	−0.087	12.934	0.227
11	−0.021	−0.032	12.959	0.296
12	−0.163	−0.160	14.490	0.271
13	0.048	−0.270	14.626	0.331
14	0.147	−0.228	15.988	0.314
15	0.131	0.054	17.110	0.312
16	−0.301	−0.175	23.331	0.105

(lnCR)

Date: 03/29/17 Time: 23:00
Sample: 1973 2013
Included observations: 37
Q-statistic probabilities adjusted for 4 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	−0.312	−0.312	3.9027	0.048
2	−0.120	−0.120	3.9080	0.142
3	−0.094	−0.152	4.2812	0.233
4	−0.058	−0.163	4.4263	0.351
5	0.028	−0.078	4.4625	0.485
6	−0.100	−0.177	4.9263	0.553
7	−0.070	−0.244	5.1612	0.640
8	0.063	−0.138	5.3589	0.719
9	0.037	−0.095	5.4305	0.795
10	−0.042	−0.187	5.5250	0.853
11	0.164	0.034	7.0152	0.798
12	−0.083	−0.063	7.4094	0.829
13	−0.157	−0.322	8.8997	0.780
14	0.083	−0.188	9.3271	0.810
15	0.066	−0.049	9.6147	0.843
16	0.030	−0.095	9.6752	0.883

*Probabilities may not be valid for this equation specification.

(lnCOT)

Upper middle income group (UMC)

Date: 03/29/17 Time: 23:24
Sample: 1973 2013
Included observations: 37
Q-statistic probabilities adjusted for 3 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	−0.450	−0.450	8.1100	0.004
2	0.115	−0.109	8.6569	0.013
3	−0.253	−0.310	11.365	0.010
4	−0.027	−0.379	11.396	0.022
5	0.005	−0.355	11.397	0.044
6	0.253	−0.018	14.369	0.026
7	−0.182	−0.224	15.966	0.025
8	0.071	−0.261	16.218	0.039
9	0.053	0.100	16.363	0.060
10	−0.191	−0.142	18.304	0.050
11	0.151	−0.085	19.562	0.052
12	−0.000	0.132	19.562	0.076
13	−0.187	−0.224	21.664	0.061
14	0.139	−0.253	22.878	0.062
15	−0.012	−0.144	22.888	0.087
16	0.035	−0.136	22.971	0.115

*Probabilities may not be valid for this equation specification.

(lnC)

Date: 03/29/17 Time: 23:51
Sample: 1973 2013
Included observations: 37
Q-statistic probabilities adjusted for 3 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	−0.170	−0.170	1.1521	0.283
2	−0.443	−0.486	9.2371	0.010
3	0.093	−0.136	9.6057	0.022
4	0.101	−0.168	10.054	0.040
5	−0.061	−0.116	10.220	0.069
6	−0.051	−0.139	10.343	0.111
7	−0.043	−0.207	10.432	0.165
8	−0.008	−0.227	10.435	0.236
9	0.251	0.113	13.693	0.134
10	−0.073	−0.055	13.977	0.174
11	−0.109	0.091	14.633	0.200
12	0.011	−0.044	14.639	0.262
13	−0.110	−0.225	15.371	0.285
14	−0.061	−0.308	15.608	0.338
15	0.282	0.049	20.811	0.143
16	−0.087	−0.192	21.328	0.166

*Probabilities may not be valid for this equation specification.

(lnCR)

Date: 03/30/17 Time: 00:02
Sample: 1973 2013
Included observations: 37
Q-statistic probabilities adjusted for 3 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	−0.555	−0.555	12.336	0.000
2	−0.033	−0.493	12.382	0.002
3	0.163	−0.263	13.508	0.004
4	−0.208	−0.455	15.405	0.004
5	0.338	0.016	20.555	0.001
6	−0.233	0.055	23.081	0.001
7	−0.105	−0.147	23.614	0.001
8	0.216	−0.163	25.929	0.001
9	−0.017	0.099	25.943	0.002
10	−0.127	−0.106	26.801	0.003
11	0.158	0.161	28.180	0.003
12	−0.239	−0.103	31.478	0.002
13	0.171	−0.189	33.233	0.002
14	0.001	−0.362	33.233	0.003
15	−0.037	−0.017	33.322	0.004
16	0.013	−0.112	33.333	0.007

*Probabilities may not be valid for this equation specification.

(lnCOT)

Lower middle income group (LMC)

Date: 03/30/17 Time: 07:05
Sample: 1973 2013
Included observations: 37
Q-statistic probabilities adjusted for 2 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	0.260	0.260	2.7132	0.100
2	−0.081	−0.160	2.9869	0.225
3	−0.362	−0.325	8.5370	0.036
4	−0.436	−0.327	16.841	0.002
5	−0.297	−0.275	20.826	0.001
6	0.038	−0.089	20.892	0.002
7	0.192	−0.142	22.670	0.002
8	0.210	−0.168	24.865	0.002
9	0.161	−0.098	26.201	0.002
10	−0.115	−0.319	26.907	0.003
11	−0.004	0.027	26.907	0.005
12	−0.058	−0.115	27.102	0.007
13	−0.011	−0.081	27.109	0.012
14	0.033	−0.036	27.177	0.018
15	0.058	−0.008	27.400	0.026
16	−0.084	−0.105	27.890	0.033

*Probabilities may not be valid for this equation specification.

(lnC)

Date: 03/30/17 Time: 07:11
Sample: 1973 2013
Included observations: 37
Q-statistic probabilities adjusted for 4 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	−0.322	−0.322	4.1520	0.042
2	−0.144	−0.276	5.0057	0.082
3	−0.026	−0.210	5.0335	0.169
4	−0.069	−0.254	5.2433	0.263
5	−0.037	−0.288	5.3040	0.380
6	0.086	−0.201	5.6468	0.464
7	0.083	−0.090	5.9812	0.542
8	−0.102	−0.198	6.4980	0.592
9	0.120	−0.003	7.2407	0.612
10	−0.078	−0.059	7.5656	0.671
11	−0.101	−0.150	8.1264	0.702
12	0.022	−0.171	8.1538	0.773
13	0.182	0.062	10.151	0.682
14	−0.200	−0.201	12.654	0.554
15	0.133	−0.023	13.807	0.540
16	−0.011	−0.066	13.815	0.612

*Probabilities may not be valid for this equation specification.

(lnCR)

Date: 03/30/17 Time: 07:18
Sample: 1973 2013
Included observations: 37
Q-statistic probabilities adjusted for 2 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	0.027	0.027	0.0285	0.866
2	−0.227	−0.228	2.1528	0.341
3	−0.334	−0.338	6.8810	0.076
4	−0.066	−0.144	7.0691	0.132
5	−0.068	−0.282	7.2804	0.201
6	0.004	−0.261	7.2810	0.296
7	0.116	−0.137	7.9238	0.339
8	0.104	−0.161	8.4669	0.389
9	0.109	−0.026	9.0828	0.430
10	−0.225	−0.339	11.796	0.299
11	−0.092	−0.252	12.269	0.344
12	0.220	0.104	15.070	0.238
13	0.018	−0.232	15.089	0.302
14	−0.029	−0.067	15.143	0.368
15	0.052	0.181	15.320	0.429
16	−0.005	−0.015	15.321	0.501

*Probabilities may not be valid for this equation specification.

(lnCOT)

Group of countries do not have serial-correlation if most of the probabilities are significant ($p < 1$).

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